

Anomaly Detection for Predictive Maintenance in Industrial Robots

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Background

Anomaly detection in industrial robots is of vital importance in **manufacturing environments** as it ensures early identification of potential failures, reduces downtime, enhances safety, and maintains product quality.

By leveraging **machine learning algorithms**, manufacturers can proactively address irregular behaviors in robotic systems, leading to more efficient operations and significant cost savings.

Real-world manufacturing environments oftentimes do not have **sufficient amounts of historical data** from which to learn anomalous patterns.

This work, performed in collaboration with **VDL Nedcar** and **VDL Steelweld**, investigates the use of **synthetically injected anomalies** for the development of machine learning anomaly detection models.

We **demonstrate the viability** of using synthetically injected anomalies by comparison against real-world anomalies **simulated in a surrogate robot**.

This work provides the first steps towards **synthetic dataset generation** using surrogates in production line environments.

Problem Definition

VDL Nedcar and VDL Steelweld have developed a new demonstration **production line** for configurable battery packs.



Figure 1: Robot at VDL Nedcar for applying closing plate to the battery pack.

They would like to develop data-driven **machine learning models** for detecting anomalies in their robots.

VDL Nedcar possesses robots for which years of historical data exists. This data, however, does not have **labelled anomalies** and simulation of such data is **prohibitively expensive**. **Synthetic anomalies** must be **injected** into the data.

In this work, we investigate how machine learning models trained on synthetically injected anomalies can be **evaluated**.

Proposed Solution

A **surrogate robot** will be built that mimics the functions of production line robots. **Real-world anomalies** will be simulated on the surrogate robot. **Synthetic anomalies** will be **injected** to data that contains no anomalies. Machine learning models will be trained to detect anomalies in both scenarios.

Results from synthetic and real-world anomalies will be analyzed through **their precision-recall curves**. Curves which show similar patterns in synthetic and real-world data will provide evidence to the correspondence between synthetic and real-world anomalies.

Acknowledgement

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Methodology

Three types of synthetic anomalies were injected with consultation from domain experts: **point**, **sinusoidal**, and **Gaussian**. Anomalies were generated with **differing sizes** to simulate various severities.

Corresponding real-world anomalies were simulated using a **custom EDMO robot** as shown in Figure 2.

Four common **machine learning anomaly detection methods** were trained on the synthetic and real-world data: Z-scores (Z), modified Z-scores (MZ), local outlier factor (LOF), and isolation forest (IF).

Precision-recall (PR) curves were obtained and compared as shown in Figure 3.

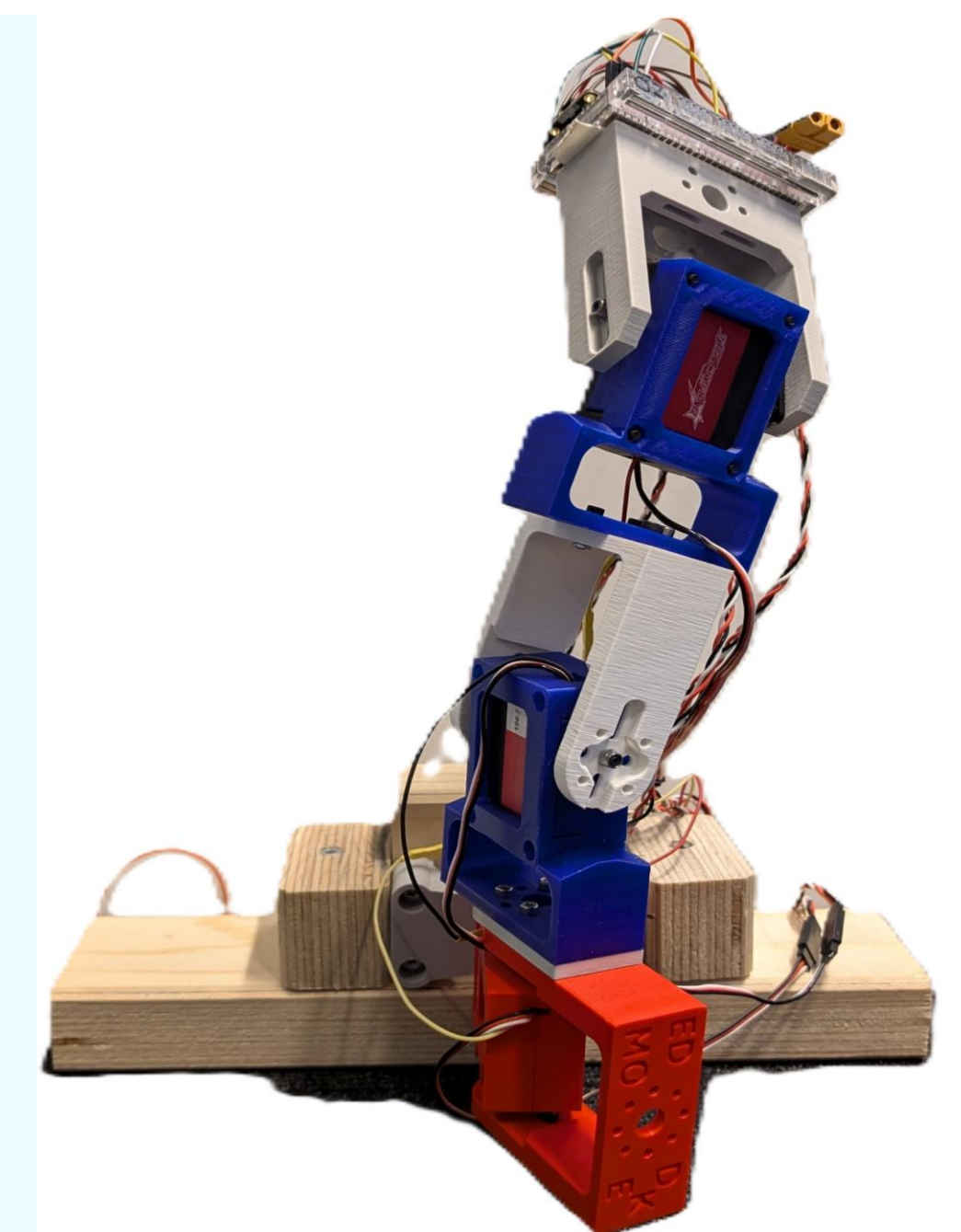


Figure 2: EDMO robot.

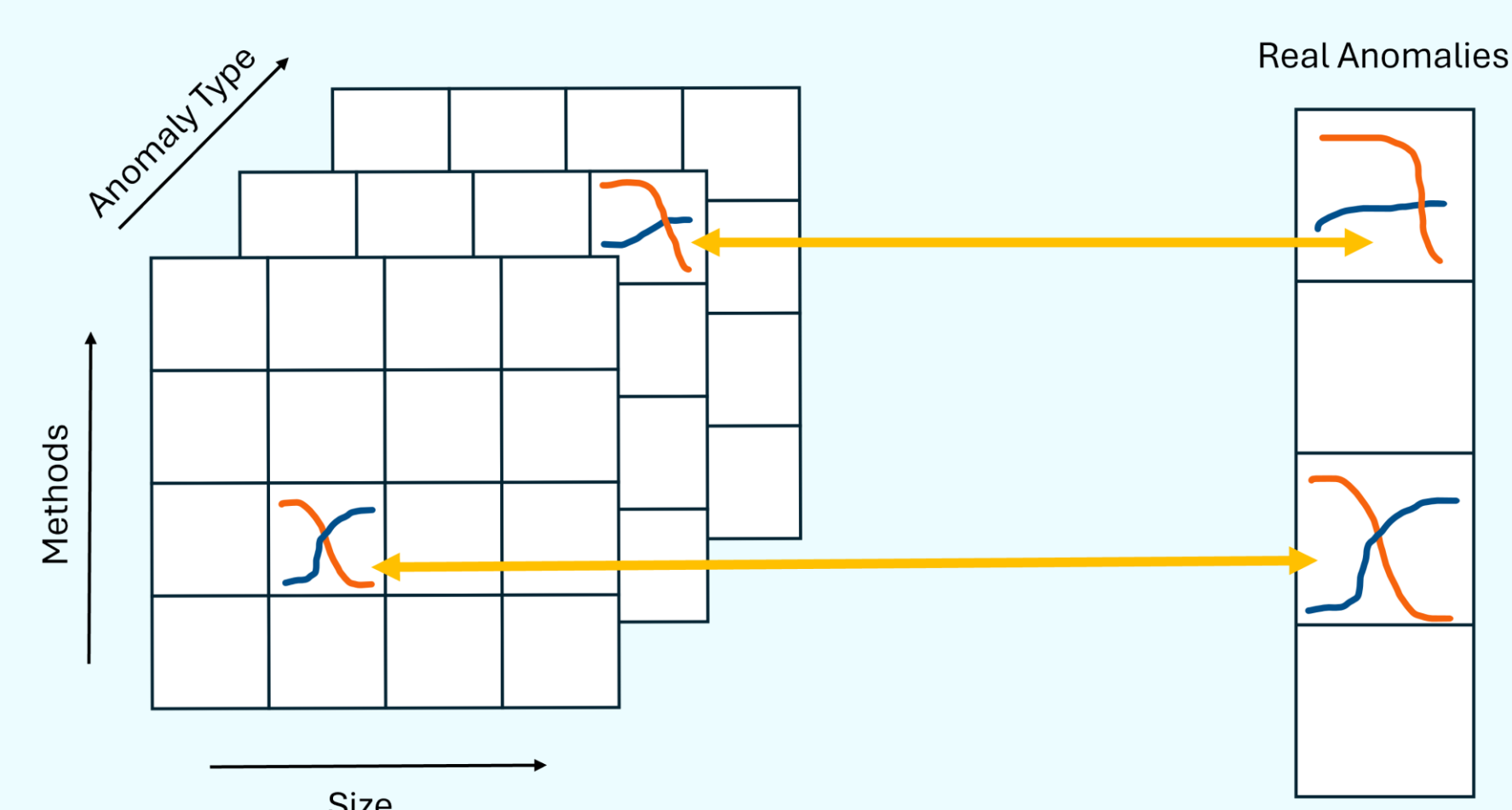


Figure 3: Proposed PR curve evaluation framework.

Results

PR curve analysis demonstrates that synthetic anomalies generated with domain knowledge can exhibit **similar patterns** as real-world anomalies. Below is an example of the PR curves of Gaussian synthetic anomalies of various sizes (Figure 4) and the corresponding real-world anomaly (Figure 5). In this case, an anomaly size of 0.5 best captures real-world anomalies.

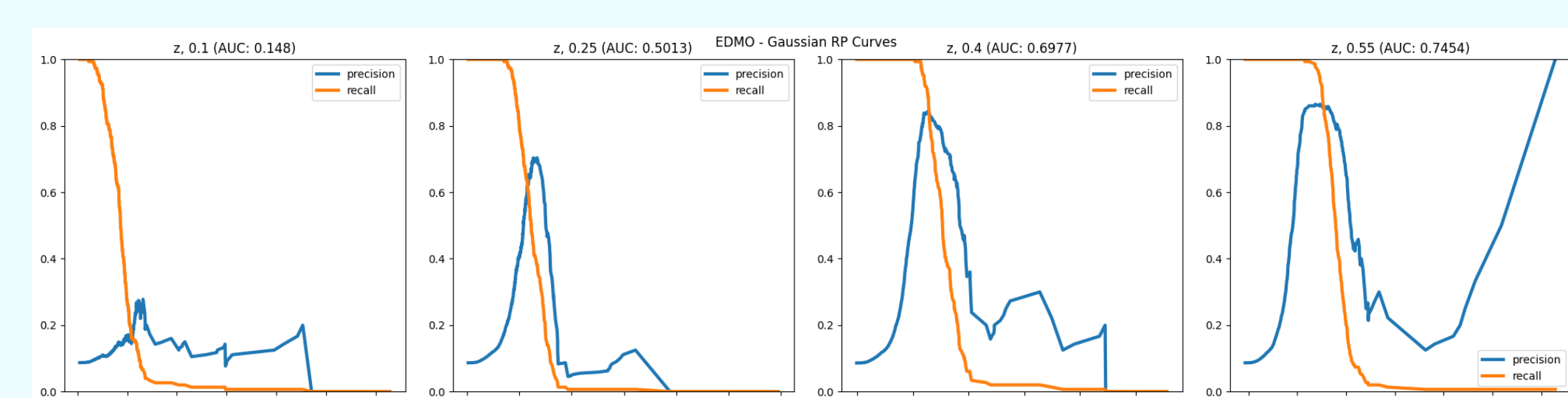


Figure 4: Z-score PR curves of Gaussian synthetic anomalies of various sizes.

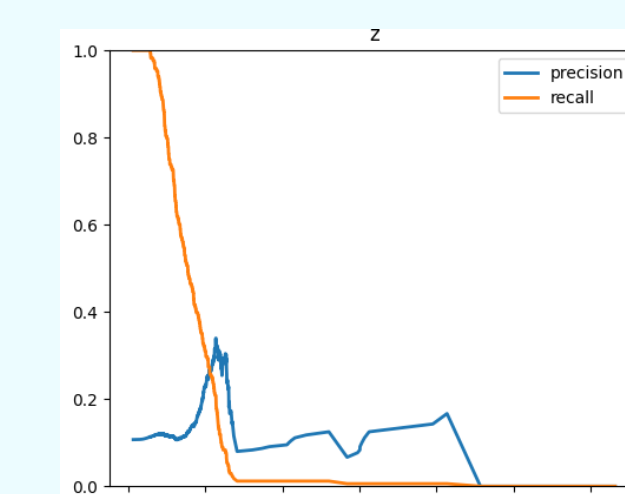


Figure 5: Real-world Z-score PR Z-scores.

Future Work

Currently, we rely on manual inspection for PR-curve comparison. Future work should make use of a more rigorous, **automated matching process**. Furthermore, an analysis of how well insights gained from surrogate robots **transfer to production robots** needs to be performed.



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